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Extreme temperature analysis under forest cover compared to an open field

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ABSTRACT

We analyse air temperature data from 14 sites in Switzerland, each with two weather stations in close proximity, one under a forest canopy and the other in the open. We use the statistics of extremes to investigate how extremely high maximum and extremely low minimum temperatures depend on the effect of forest cover. Our analysis shows that temperature maxima at two nearby stations are less dependent than are temperature minima. Maxima under the canopy are influenced by altitude: for higher sites, the maxima are less variable and depend less on the open-field data. Southerly orientations increase the dependence of minimum temperatures and so reduce the sheltering effect during cold periods. Extreme maximum and minimum temperatures occur less within conifer forests, indicating that the insulation provided by conifers all over the year is more efficient than that provided by deciduous species. Steepness of slopes has a complex impact on distributions of extremes and on their dependence.

1. Introduction

Climate change research is focusing increasingly on rare events, owing to the realisation that they may change more than averages and that their effects may therefore be much more damaging than in the past. Katz and Brown (1992) pointed out their importance, and showed that changes in their occurrence may depend more on changes in variability than on changes in averages. Among the publications that have tackled this problem, Schär et al. (2004) showed that climate change is not limited to a warmer mean and that an increase in the variability may be able to account for heat waves like that of summer 2003 (see also, Scherrer et al., 2005). The 2007 Assessment Report of the Intergovernmental Panel on Climate Change has stressed past and future changes in the extremes and the importance of their potential impacts. Since their effects on vegetation are already becoming visible (Walther et al., 2002; Zimmermann et al., 2009), we need a better understanding of the mechanisms that govern the occurrence of extreme events under the canopy.

The impact of temperature extremes on ecological processes in general (Stenseth et al., 2002) and on forest ecosystems in particular may be more important that those of temperature averages (Friedenberg et al., 2008; Jentsch and Beierkuhnlein, 2008; Lebourgeois et al., 2005). Temperature and temperature extremes are strongly influenced by vegetation cover, as forested areas usually cool down less during the night and limit daytime air warming (Chen et al., 1993; Flemming, 1995; Geiger et al., 2003; Grimmond et al., 2000; Lee, 1978; Oke, 1987; Rambo and North, 2009). The influence of forest canopy cover depends on the tree species and on the exposure, but also on the temperature itself (Renaud and Rebetez, 2009). Thus the impact of vegetation cover on temperature extreme values can be expected to be different from its impact on average values. If we wish to understand the potential impact of climate change on forests, we require more insight into the specific impact of different vegetation cover types on temperature extremes.

The objective of the present study is to compare below-canopy and open-site temperature extremes in order to determine the impact of the forests on particularly high maximum or low minimum temperatures. Temperature values are analysed in connection with different characteristics of the forests so as to bring to light their roles in the mechanisms of extremes. The purpose of this paper is to use statistical methods for analysis of extreme events to provide a quantitative understanding of how these characteristics influence the regime of extremes and the dependence in the extremes. After a preprocessing step consisting in removing annual trends, the data were transformed to have unit Fréchet marginal distributions, so that bivariate extreme value distributions could be fitted to threshold exceedances, and other tools from statistics of extremes could be brought to bear.

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2. Data and methods

2.1. LWF data set

We analysed the Long-term Forest Ecosystem Research (LWF) data set, which comprises meteorological measurements from 17 sites from all parts of Switzerland, 14 of which had enough data for this study. At each site, data are recorded at two meteorological stations close to each other and with comparable topographic characteristics, one under forest cover and one in an open field. Data have been recorded every 10 min since 1997, temperature being measured 2 m above ground in circular metal shelters. This database consists of daily measurements from all biogeographical zones of Switzerland, with different orientations, elevations and forest types, and represents therefore a particularly rich source of data.

The dataset covers the possible ranges of the different characteristics quite well (see Table 1). The altitude ranges from 480 to 1900 m above sea level (a.s.l.). The forests are managed according to two different systems: either a high forest, with high boles; or a former coppice, in which trees were once cut close to base and shoots regrew from stools, giving dense undergrowth. The orientation comprises six directions with North and South predominant. The slopes form four groups: less than 14% (four sites), between 27 and 35% (four sites), between 58 and 68% (five sites) and one with 80% (Visp). We consider three different types of humus/soils: mull (thin and humid humus) and for other humus forms, soils that are mainly podzolic (thick and humid humus, acidic) and soils that are calcareous (thick and dry humus). The forest types fall into four groups: Beech only, Beech and Silver Fir, Oak (or Silver Fir and Oak) and conifers (Spruce, Larch and Arolla Pine, Mugo Pine, Scots Pine). Finally, all the five bio-geographical zones of Switerland are represented. These features are obviously correlated, since, for example, a particular tree species will not grow at any altitude and on any soil. The high quality of the LWF data has been verified through a comparative study with data from MeteoSwiss stations by Logeay and Rebetez (1999). For more details on the location of the sites and their features, see Renaud and Rebetez (2009).

2.2. Preprocessing

The statistical analysis of our data consists first of preprocessing to obtain stationary independent series, and, second, application of methods for bivariate extremes to the resulting series. This way to proceed allows us to consider the maximum temperatures that occur in winter as well as the minimum temperatures measured in summer. In this section we describe the preprocessing step.

We work separately with the daily maximum and daily minimum temperature series for each site, but we describe the preprocessing only for the maxima, as the same procedure was applied to the minima. We denote maximum temperature by $t_{d,y,s}$, where day d runs from 1 to 365, year y runs from 1996 to 2007, and station s runs from 1 to 28. After checking that they were not outlying, we removed measurements for February 29.

Extreme value analysis requires stationary series. To remove seasonal variation from the data we first estimated a smooth annual cycle by fitting a periodic cubic spline (Ruppert et al., 2003) to the 365 daily average temperatures. Some tuning suggests that splines with 6 degrees of freedom are appropriate. We then obtained a residual time series $t_{d,y,s} - \tilde{t}_{d,s}$, where $\tilde{t}_{d,s}$ denotes the fitted spline, and then applied the same procedure to the 365 daily variances of the residuals, obtaining fitted splines $\tilde{v}_{d,s}$ for the variances; in this case 4 degrees of freedom seem to be adequate, as the variances change less than do the averages. The fitted splines can then be used to obtain stationary series

$$\hat{t}_{d,y,s} = \frac{(t_{d,y,s} - \tilde{t}_{d,s})}{\tilde{v}_{d,s}^{1/2}}, \quad d = 1, \ldots, 365, \quad y = 1996, \ldots, 2007, \quad s = 1, \ldots, 14, \tag{1}$$

whose extremal properties can be analysed using the appropriate statistical tools.

Before performing an extremal analysis, and in order to assess whether the fitted splines may be linked to the features of the site, we computed the maximum difference between the splines for the mean temperatures for the two stations at each site,

$$\max_d(\tilde{t}_{d,s_2} - \tilde{t}_{d,s_1}), \tag{2}$$

and the amplitude of this difference

$$\max_d(\tilde{t}_{d,s_2} - \tilde{t}_{d,s_1}) - \min_d(\tilde{t}_{d,s_2} - \tilde{t}_{d,s_1}), \tag{3}$$

where s_1 and s_2 denote respectively the station under forest cover and the station in the open field. We consider (2) to be an indicator of the intensity of the cooling shelter and (3) to be an indicator of the variability of this intensity over the year. As the degrees of freedom of the splines are so low, we can ignore the variation in $\tilde{t}_{d,s}$ and $\tilde{v}_{d,s}$, and therefore in (2) and (3).

As a second preprocessing step we check for long-term dependence in the temperature residuals (1) by fitting to them autoregressive models of order p, AR(p), models (Shumway and Stoffer, 2000, Chapter 3), with the order p selected by minimising the Akaike Information Criterion, AIC. Since a majority of the fits are of order $p = 3$, we chose to fit an AR(3) model

$$\hat{t}_{j,s} = \phi_1 \hat{t}_{j-1,s} + \phi_2 \hat{t}_{j-2,s} + \phi_3 \hat{t}_{j-3,s} + \varepsilon_{j,s}, \quad j = 1, \ldots, n_s,$$

where n_s is the number of measurement days at station s, to every series. To check the goodness of fit we apply a standard procedure based on the cumulative periodogram of the residuals (Venables and Ripley, 1994, Section 14.2), which indicates that the model is adequate. The implication of this is that the stationary series (1) do not display long-term dependence, which would vitiate the application of standard extreme-value methods, as outlined in the next section.

2.3. Univariate analysis of extremes

Statistics of extremes concerns the analysis of the tails of distributions. Although the assumption of Gaussianity is commonly made in statistical analyses, the Gaussian distribution typically fits the lower and upper tails of a dataset poorly, and a variety of specialised more appropriate techniques have been developed, based on mathematical characterisations of the tail behaviour of probability distributions (Beirlant et al., 2004). Below we outline the ideas necessary for our analysis in the context of the upper tail of the data, the largest values, but the same ideas may be applied to the lower tail by analysing the upper tail of the negated data, and then back-transforming the results.

One standard approach to fitting the upper tail of a univariate probability distribution, known as the peaks over threshold method, involves fitting the generalized Pareto distribution to those observations X that are greater than a high threshold, u. This procedure is mathematically justified by theorems which establish that if there exists a nondegenerate limiting distribution for the rescaled exceedance $X_u = (X - u)/a(u)$, where $a(u) > 0$ and the threshold u increases towards the upper support point x_F of X, then the distribution of X_u must approach the generalized Pareto distribution

$$H(x_u) = \begin{cases} 1 - [(1 + \xi x_u/\sigma)_+]^{-1/\xi}, & \xi \neq 0, \\ 1 - \exp(-x_u/\sigma), & \xi = 0, \end{cases} \quad \sigma > 0, \quad \xi \in R, \tag{4}$$

Table 1
Characteristics of the sites. The columns are: site name; altitude (m a.s.l.); system management (F. Coppice stands for former coppice); orientation; slope (%); humus type (or soil type for humus that are not mull); tree species; and bio-geographical zone (L. Alps stands for lower Alps and S. Alps for southern Alps).

Name	Alt.	Management	Or.	Slope	Soil	Species	Zone
Beatenberg	1500	High Forest	SW	33	Podzolic	Spruce	L. Alps
Bettlachstock	1150	High Forest	S	66	Mull	Beech, Silver Fir	Jura
Celerina	1890	High Forest	NE	34	Podzolic	Larch, Arolla Pine	Alps
Chironico	1350	High Forest	N	35	Podzolic	Spruce	S. Alps
Isone	1200	F. Coppice	NE	58	Podzolic	Beech	S. Alps
Jussy	500	F. Coppice	flat	3	Mull	Oak	Plateau
Lausanne	800	High Forest	NE	7	Mull	Beech, Silver Fir	Plateau
Nationalpark	1900	High Forest	S	11	Calcareous	Mugo Pine	Alps
Neunkirch	600	F. Coppice	N	58	Mull	Beech	Jura
Novaggio	950	F. Coppice	S	68	Podzolic	Oak	S. Alps
Othmarsingen	490	High Forest	S	27	Mull	Beech	Plateau
Schänis	750	High Forest	W	60	Mull	Beech, Silver Fir	L. Alps
Visp	700	High Forest	N	80	Calcareous	Scots Pine	Alps
Vordemwald	480	High Forest	NW	14	Mull	Silver Fir, Oak	Plateau

where we write $c_+ = \max(c, 0)$. The two parameters of H are a scale parameter σ, which controls the variability of the limiting distribution, and the shape parameter ξ, which determines the shape of the distribution, and, in particular, the weight of its tail. The limiting tail of a Gaussian distribution has $\xi = 0$, but (4) allows heavier-tailed distributions, corresponding to positive ξ, and lighter-tailed distributions, for which ξ is negative; in this case H allows values only in the interval $(0, -\sigma/\xi)$, so there is an upper bound to the limiting distribution. Although the presence of $a(u)$ is required for the mathematical derivation of (4), for statistical purposes it may be absorbed into σ, which must be estimated.

In practice this mathematical result is applied by using the data $x_1, \ldots, x_n$ to choose a threshold u, and then using maximum likelihood estimation to fit the distribution (4) to exceedances over u. Typically the fitted distribution $\hat{H}$ fits well for a sufficiently high threshold u, sometimes taken to be the 0.9, 0.95, or 0.98 quantile of the data, and the estimated shape parameter generally satisfies $|\hat{\xi}| < 1$. Further statistical elements may be found in Davison and Smith (1990) or in Coles (2001, Chapter 4).

In the next section we describe joint statistical analysis of the extremes of the temperature data from the two stations at each site. It is conventional for such bivariate analysis to put the extremes in a standard form, obtained by using the fitted generalized Pareto distributions to transform the tails of the distribution. This is performed through an empirical transformation based on the sample $x_1, \ldots, x_n$, in which the transformed values are $y_j = -1/\log \hat{F}(x_j)$, where

$$\hat{F}(x) = \begin{cases} n_x/n, & x \le u, \\ n_u/n + n^{-1}(n - n_u)\hat{H}(x-u), & x > u, \end{cases} \quad (5)$$

in which $n_x = \#\{j : x_j \le x\}$ is the number of observations that do not exceed x. The distribution of the $y_1, \ldots, y_n$ is then well-approximated by the unit Fréchet distribution, $\exp(-1/y)$, for $y > 0$.

2.4. Bivariate analysis of extremes

We used the evd package (Stephenson, 2002) of the statistical environment R (R Development Core Team, 2009) to fit a variety of bivariate extreme value distribution functions to the threshold exceedances of the stationary series (1), i.e. $\{\hat{t}_{d,y,s} : \hat{t}_{d,y,s} > u_s\}$, where u_s is sufficiently high threshold. We fitted a variety of models with the thresholds u_s corresponding to the 90%, 95% and 98% quantiles of $\hat{t}_{d,y,s}$ and the parameters of the model estimated by maximum likelihood. The best overall fit to the bivariate temperature series for the 14 pairs of stations was obtained with the asymmetric logistic distribution (Beirlant et al., 2004; Tawn, 1988)

$$G(y_{j1}, y_{j2}) = \exp\left[-(1-\tau_1)y_{j1} - (1-\tau_2)y_{j2} - \left\{(\tau_1 y_{j1})^{1/\rho} + (\tau_2 y_{j2})^{1/\rho}\right\}^{\rho}\right], \quad y_{j1}, y_{j2} > 0, \quad (6)$$

where $0 < \rho \le 1$, $0 \le \tau_1, \tau_2 \le 1$. For simplicity, we will drop the j subscripts and write y_1 and y_2 to designate two values of the bivariate series like in $G(y_1, y_2)$. The model (6) has three parameters, ρ, τ_1 and τ_2, so, including the values ξ and σ for each of the two marginal distributions, there are seven parameters overall. The parameter ρ controls the overall dependence between the variables, with complete independence corresponding to $\rho = 1$ and dependence increasing as $\rho \to 0$. When $\tau_2 = \tau_1$, the probability density function is symmetric, whereas if $\tau_1 > \tau_2$, this density is higher on the side corresponding to the first index, and conversely if $\tau_2 > \tau_1$. Independence is obtained when $\rho = 1$, $\tau_1 = 0$ or $\tau_2 = 0$. Complete dependence is obtained when $\tau_1 = \tau_2 = 1$ and ρ approaches zero. The fact that model (6) provides the best fit means that even after preprocessing it is necessary to account for asymmetries in the occurrences of extreme events between the stations at a site, as shown by the left panel of Fig. 1.

For graphical insight into the dependence structure of our series, we use the Pickands dependence function (Beirlant et al., 2004). In the bivariate case, this can be defined by

$$A(t) = -\log G_*\left(\frac{1}{1-t}, \frac{1}{t}\right), \quad t \in [0, 1],$$

where G_* is a bivariate extreme value distribution with standard Fréchet marginal distributions, such as (6). The justification of this definition is quite technical (Beirlant et al., 2004, Section 8.2.5), but in brief it turns out that any bivariate extreme value distribution function can be written in the form

$$G(y_1, y_2) = \exp\left[\log\left\{G(y_1, \infty)G(\infty, y_2)\right\} A\left(\frac{\log G(\infty, y_2)}{\log\{G(y_1, \infty)G(\infty, y_2)\}}\right)\right],$$

so a plot of $A(t)$ is a useful visual summary of the dependence between the variables, as we shall see below, where we use plots of the fitted functions A to compare and contrast the dependence of the maxima and minima at the different sites. The Pickands dependence function is convex and satisfies

$$\max\{1-t, t\} \le A(t) \le 1, \quad t \in [0, 1]. \quad (7)$$

The lower bound in (7) corresponds to complete dependence,

$$G(y_1, y_2) = \min\{G_1(y_1), G_2(y_2)\}, \quad y_1, y_2 > 0,$$

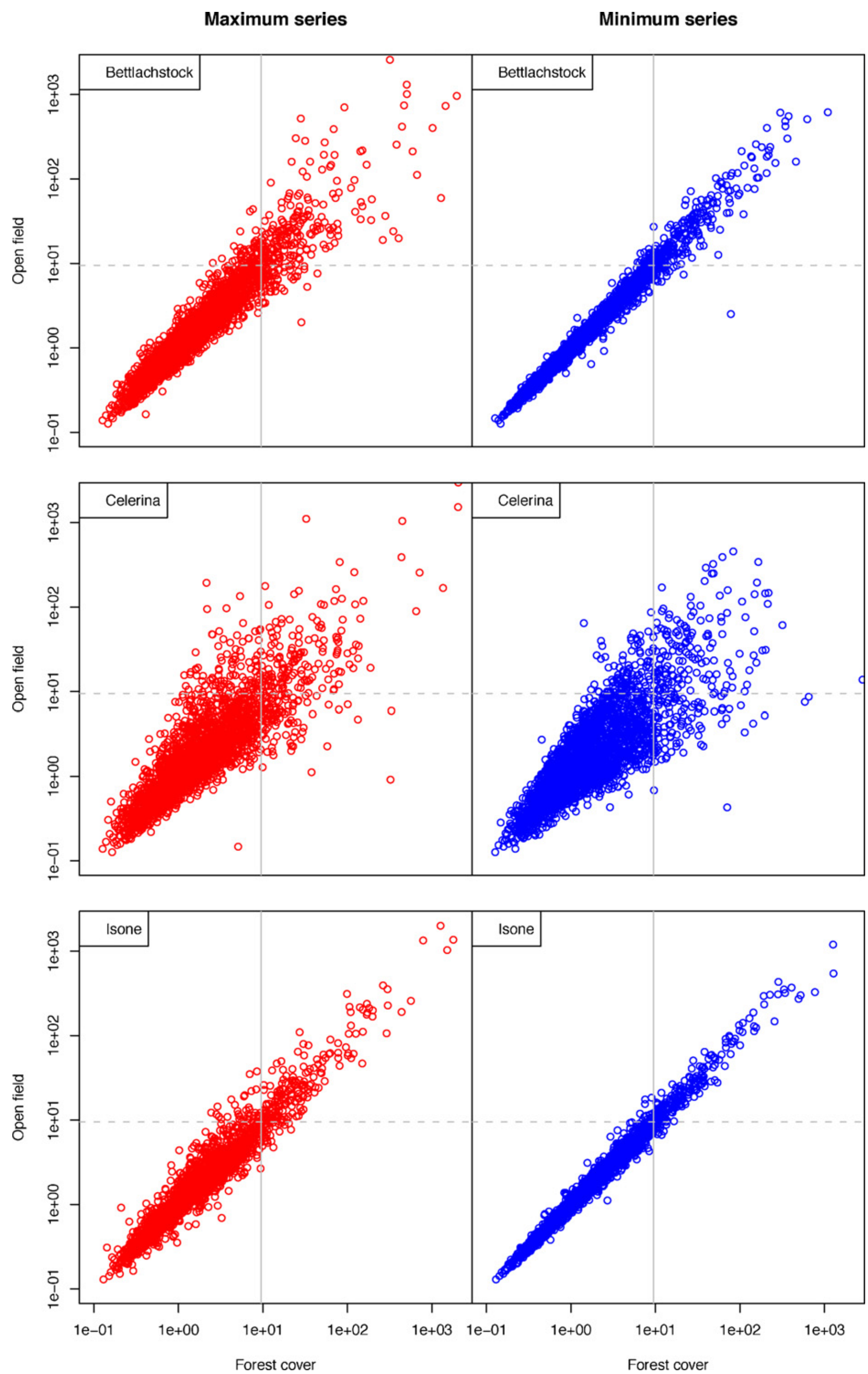

Fig. 1. Plot of the four series measured at three sites: Bettlachstock, Celerina and Isone, after transformation to unit Fréchet scale. The grey horizontal and vertical lines correspond to the thresholds. Note the logarithmic axes.

whereas the upper bound $A(t) = 1$ corresponds to independence,

$$G(y_1, y_2) = G_1(y_1)G_2(y_2), \quad y_1, y_2 > 0.$$

The classical theory of extremes, elements of which are sketched above, has been extended in recent years to so-called near-independence cases (see Beirlant et al., 2004, Section 9.5; Coles, 2001, Section 8.4), whose presence can be detected using standard diagnostic tools. Giving the details of these would take us too far afield, but since all the results and discussion in the following sections presuppose that the classical theory applies, we applied these diagnostics to our data, and found no evidence that the classical theory is invalid.

3. Results

The series for the two stations of a site can be plotted using the same scale for each marginal distribution, as in Fig. 1, which shows the transformed maxima and minima after applying the transformation (5) to the preprocessed series for the two stations at three sites: Bettlachstock, Celerina and Isone. The grey lines show thresholds at the 90% quantiles, which determine the extreme observations. The bivariate minima and maxima both show strong dependence, though the tighter concentration of points along the leading diagonal shows that the dependence of the minima is appreciably stronger; these plots are quite symmetric whereas the weaker dependence of the maxima is shown by the greater spread at high levels. The data from Celerina are somewhat different from those at the other two sites; we return to this below.

3.1. Preprocessing

Linking the obtained trends to the site features allows us to draw preliminary conclusions. The first two columns of Table 2 show the maximum difference between the two splines, Eq. (2), and the amplitude of this difference, Eq. (3), for each site. The first column indicates the maximum intensity of the cooling shelter, and the second is linked to the variability of this intensity over the year. The fitted splines, and hence temperature trends, are much more similar for the temperature minima than for the maxima for all the sites except Celerina and Visp: the maximum difference between the splines ranges from 1.24 °C to 3.58 °C for the maximum temperatures and from 0.02 °C to 2.60 °C for the minimum temperatures. Excluding Celerina, the maximum difference for the minimum temperatures lies between 0.02 °C and 1.25 °C. Concerning the amplitudes, the values for the maximum temperatures lie between 1.29 °C and 3.10 °C and those for the minimum temperatures between 0.25 °C and 1.09 °C (except Celerina), also showing the greater similarity of the splines for the minimum temperatures.

Both the maximum differences between the splines and the amplitudes of these differences are correlated with some of the features, as shown in Fig. 2. The effect of species on amplitude is fairly uniform, but there appear to be some systematic patterns for the maximum differences. The cooling effect of vegetation is generally slightly larger with beech (3.27 °C on average) than with oaks or conifers (2.29 °C on average), and it increases with the slope (0.13 °C each 10% if we exclude Nationalpark, Novaggio and Visp, whose values are clearly outlying). The two sites with calcareous soil have smaller differences (1.35 °C and 1.59 °C) than the others (2.92 °C on average). Three sites have a particularly low difference: Nationalpark, Novaggio and Visp (1.35 °C, 1.24 °C and 1.59 °C compared to 3.07 C on average for the others). Altitude does not seem to be linked to the values of these indicators. The forest species play an important role: the lower left panel of Fig. 2 shows that the cooling shelter of conifers is more regular through the year (conifer sites have a mean amplitude of 1.70 °C) than the shelter of deciduous trees, the variation of which is larger (2.17 °C on average). Moreover, the impact of conifer forests is larger in winter, whereas deciduous forests have a larger impact in summer.

The differences between the splines are much smaller for the temperature minima: −0.36 °C on average for the minimum temperatures (0.54 °C if the absolute values of the maximum distances are considered) and 2.71 °C on average for the maximum temperatures, as shown in Fig. 3. Celerina stands out from the other sites: it is the only one where the difference is greater in winter, indicating that unlike at all the other sites, the effect of forest sheltering at Celerina is stronger in winter. Three characteristics appear to be necessary to get a strong cooling effect: conifer species (−0.90 °C on average at sites with conifers against −0.06 °C otherwise), a northerly orientation (−0.66 °C for the northerly oriented sites against −0.06 °C for the others), and a high forest (−0.42 °C for the high forests and −0.21 °C for the former coppices). Three sites have a northerly oriented coniferous high forest: Celerina, Chironico and Visp. Their maximum difference are −2.60 °C, −1.25 °C and −0.98 °C, while the other site differences range from −0.52 °C to 0.74 °C with an average of −0.02. The amplitudes of the differences for the minimum temperatures (0.76 °C on average) are generally smaller than for the maxima (2.00 °C on average), but may depend on the region (in the Alps, they range from 0.52 °C to 3.22 °C with a mean value of 1.60 °C, whereas in the Southern Alps they range from 0.26 °C to 0.41 °C, with a mean value of 0.32 °C) and on the orientation (1.00 °C at northerly oriented sites and 0.52 °C otherwise, on average).

The fit of the AR process gave very similar estimates for all the series; for the maximum series, we found that the autoregressive parameters $\hat{\phi}_1$, $\hat{\phi}_2$ and $\hat{\phi}_3$ lay in the intervals [0.56, 0.87], [− 0.17, 0.07] and [0.03, 0.08] respectively; according to the AIC the best order for four series was $p = 1$ and the best for seven more was $p = 2$. For the minimum series, the corresponding intervals were [0.66, 0.98], [− 0.25, − 0.08] and [0.03, 0.11], with nine series of order $p = 2$. Thus these fits suggest that the temperature on a given day has a fairly strong positive correlation with the value on the previous day, and weaker correlations with the two previous days, but has no longer-range dependence. We can therefore rule out long-range dependence of the temperatures. As the data show short-term dependence, the variances of the estimates in Table 2 and discussed hereafter are underestimated. The tendency of the data extremes to cluster can be measured by the limiting mean cluster size. One way to obtain this quantity is to inverse the extremal index of the series (Coles, 2001, Chapter 5). In our case, we obtained extremal indices ranging from 0.39 to 0.65, yielding limiting cluster sizes between 1.5 and 2.6, indicating that the standard errors in Table 2 should be multiplied by a factor of at most 1.7; doing so does not change the interpretation of the results.

3.2. Extremal analysis

Almost all the distributions, of both maxima and minima, have bounded tails since the corresponding estimated shape parameters $\hat{\xi}$ are negative, as shown in Table 2. The shape parameters for the minima lie in the range [− 0.2, 0], whereas those for the maxima lie in the range [− 0.3, 0.1], indicating that there is less variation in the shapes of the tails for the minimum temperatures. There is a similar but less marked difference for the scale parameters, which are a little less dispersed for the minima.

For the maxima, most of the sites have a negative shape parameter both under cover and in the open. The estimated asymmetry parameters $\hat{\tau}_1$ and $\hat{\tau}_2$ are mostly fairly similar, though Celerina is again unusual: the difference between its asymmetry parameters is much bigger than at the other sites, and we shall see below that its estimated Pickands function also differs a lot from the others. When the difference between the dependence parameters $\hat{\tau}_1$ and $\hat{\tau}_2$ exceeds 0.05, then $\hat{\tau}_2 > \hat{\tau}_1$, meaning that when the fitted distribution is asymmetric, the probability density function is higher in the open-field part and so a higher value is more likely to occur there.

For minimum temperatures, most of the shape parameters $\hat{\xi}$ are again negative, both under cover and in the open. The estimates of the dependence parameter $\hat{\rho}$ are generally lower than for the maxima, corresponding to stronger dependence between the extremes. Celerina, Neunkirch and Visp have large values of $\hat{\rho}$ compared to the others, indicating weaker dependence of their extremes; this is confirmed by the Pickands functions.

For each bivariate series, the Pickands dependence function (see Fig. 4) gives an illustration of the dependence structure. To better understand these plots, consider the three sites whose data are shown in Fig. 1. That figure shows that the data at Bettlachstock and Isone are more dependent than those at Celerina, and this is mirrored in their lower Pickands functions; Isone is most dependent. The minima are more dependent than are the maxima, and this corresponds to the functions for maxima in Fig. 1 being shallower than are those for the minima. If asymmetric, the Pickands

Table 2
Maximum difference and difference amplitude between splines (°C), and estimated parameters (standard errors) (×10^2) of the fitted bivariate asymmetric logistic distributions.

Site	Spline		Cover		Open		Dependence		
	max	amp	$\hat{\sigma}_1$	$\hat{\xi}_1$	$\hat{\sigma}_2$	$\hat{\xi}_2$	$\hat{\tau}_1$	$\hat{\tau}_2$	$\hat{\rho}$
Daily maxima									
Beatenberg	2.80	1.90	40 (3)	−13 (5)	32 (3)	−10 (6)	78 (3)	90 (3)	30 (2)
Bettlachstock	3.49	2.47	48 (4)	−19 (9)	33 (3)	−13 (7)	66 (3)	100 (0)	36 (3)
Celerina	2.78	1.35	36 (2)	−31 (4)	28 (2)	−14 (5)	36 (0)	100 (0)	56 (4)
Chironico	3.26	1.61	60 (5)	−19 (6)	50 (3)	−32 (4)	100 (0)	97 (5)	44 (3)
Isone	3.42	3.10	51 (4)	−8 (5)	52 (4)	−14 (5)	95 (2)	91 (3)	23 (2)
Jussy	2.54	2.07	44 (3)	−16 (4)	43 (3)	−21 (4)	87 (2)	96 (3)	29 (2)
Lausanne	2.89	2.05	35 (2)	−3 (5)	43 (3)	−19 (5)	91 (3)	93 (3)	33 (2)
Nationalpark	1.35	1.69	34 (2)	−22 (3)	34 (2)	−27 (3)	83 (3)	80 (4)	33 (2)
Neunkirch	3.13	1.57	48 (4)	−32 (7)	34 (3)	1 (10)	65 (4)	92 (4)	36 (3)
Novaggio	1.24	2.16	40 (3)	−2 (5)	39 (3)	−3 (5)	89 (3)	94 (2)	34 (2)
Othmarsingen	3.10	2.75	45 (3)	−29 (4)	38 (3)	−13 (6)	78 (4)	100 (0)	48 (3)
Schänis	3.58	2.00	44 (4)	−12 (8)	35 (3)	−15 (6)	70 (4)	100 (0)	40 (2)
Visp	1.59	1.95	42 (3)	−20 (4)	34 (2)	−18 (5)	93 (3)	92 (3)	36 (2)
Vordemwald	2.76	1.29	33 (2)	10 (5)	38 (3)	−7 (7)	76 (3)	88 (4)	33 (2)
Daily minima									
Beatenberg	0.02	0.39	47 (3)	−15 (4)	51 (3)	−15 (4)	87 (2)	98 (1)	15 (1)
Bettlachstock	0.07	0.76	40 (3)	−2 (4)	44 (3)	−9 (4)	96 (2)	86 (2)	16 (1)
Celerina	−2.60	3.22	56 (4)	−20 (4)	50 (4)	−19 (5)	88 (3)	100 (0)	41 (2)
Chironico	−1.25	0.41	48 (4)	−11 (5)	54 (4)	−17 (5)	99 (1)	92 (3)	24 (2)
Isone	0.13	0.29	46 (3)	−15 (4)	49 (4)	−17 (4)	96 (2)	95 (2)	15 (1)
Jussy	−0.52	0.59	50 (3)	−18 (4)	51 (3)	−16 (4)	95 (2)	98 (1)	20 (1)
Lausanne	0.74	0.43	47 (2)	−17 (2)	43 (2)	−13 (3)	100 (0)	94 (1)	17 (1)
Nationalpark	0.32	0.52	48 (3)	−22 (3)	46 (3)	−17 (4)	100 (0)	94 (1)	12 (1)
Neunkirch	−0.24	1.09	47 (4)	−8 (6)	59 (5)	−15 (6)	98 (3)	99 (2)	42 (3)
Novaggio	−0.19	0.26	49 (3)	−11 (4)	49 (3)	−13 (3)	95 (2)	97 (1)	21 (1)
Othmarsingen	0.09	0.87	55 (4)	−16 (4)	59 (4)	−21 (4)	97 (1)	86 (2)	15 (1)
Schänis	−0.04	0.25	36 (2)	−13 (3)	39 (2)	−17 (2)	100 (0)	93 (2)	22 (1)
Visp	−0.98	1.06	62 (4)	−23 (5)	54 (4)	−10 (6)	91 (4)	99 (3)	46 (3)
Vordemwald	−0.39	0.49	57 (4)	−14 (5)	54 (4)	−12 (5)	94 (2)	100 (0)	26 (2)

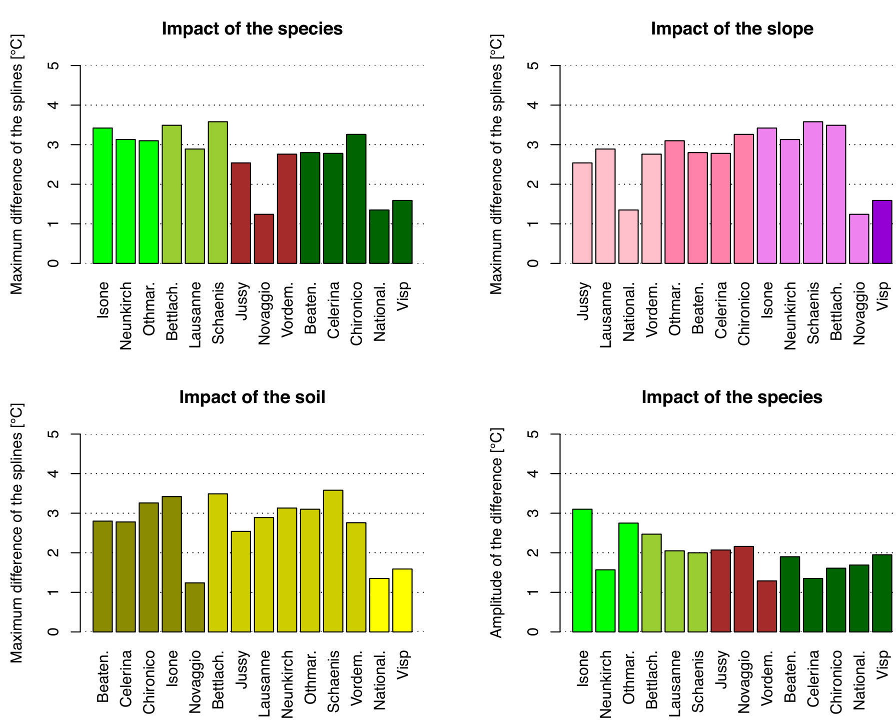

Fig. 2. Summary of spline analysis for maximum temperatures. Maximum differences between the splines as a function of forest type (top left), slope (top right) and soil (lower left); and amplitude of the difference between the splines as a function of forest type (lower right). From left to right, the forest types are: beech; beech and silver fir; oak alone or with silver fir; and conifers. From left to right, the slopes are: less than 15%; 15–35%; 35–70%; and over 70%. From left to right, the soil types are: podzolic; mull; and calcareous.

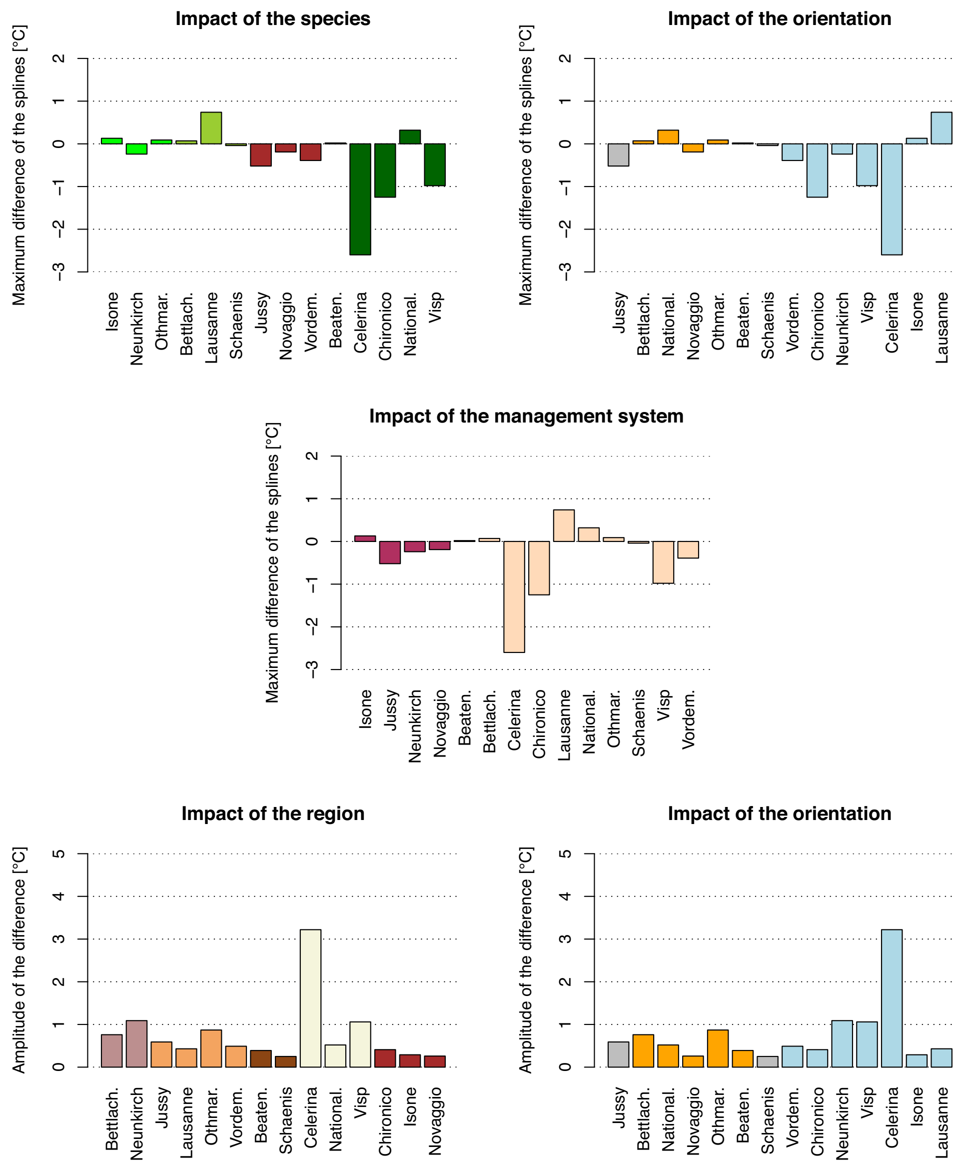

Fig. 3. Summary of spline analysis for minimum temperatures. Maximum difference between the splines as a function of forest type (top left), orientation (top right), and management system (middle), and the amplitude of the difference between the splines as a function of region (lower right) and orientation (lower left). From left to right, the forest types are: beech; beech and silver fir; oak alone or with silver fir; and conifers. The orientations are: flat or west-oriented site (grey); south-oriented site (orange); and north-oriented (light blue). The management systems are high forests (beige) and coppices (brown). From left to right, the regions are: Jura; Plateau; lower Alps; Alps; southern Alps. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

functions for maxima tend to be deeper on the right than on the left, corresponding to extreme events that are relatively rarer under forest shelter than in the open field, when they occur; cf. the panels for maxima at Bettlachstock and Celerina in Fig. 1. It is important to appreciate that these plots refer to standardized data: the transformation (5) ensures that both the data from under cover and those in the open field have the same marginal distribution, once transformed, so the Pickands functions measure any asymmetry not on the original scale, but on a transformed scale.

The impression given by Fig. 1 and less vividly by Table 2 that the minima are much more strongly related than are the maxima is confirmed by Fig. 4: the dependence functions for the minima are overall much closer to the lower bound. They are also more symmetric than are those for the maxima, which tend to be shallower on the left than on the right, corresponding to days with extreme high temperatures being relatively cooler below the canopy. This asymmetry is present in most of the plots for maxima, in varying degrees, but is less marked for the minima. Celerina is unusual: it comes closest to independence, which would correspond to the horizontal line, for maxima, and, with Visp and Neunkirch, is one of the least dependent sites for the minima.

4. Discussion

Our results describe the tail distribution (i.e. the extremal behaviour) of the maximum and the minimum daily temperatures. They show that for the maximum temperatures there is no station with a possibly positive shape parameter (i.e. a heavy-tailed distribution) higher than 1000 m above sea level: at such altitudes, extreme maximum temperatures are therefore likely to be bounded. Furthermore, among open-field stations, two shape parameters are clearly outstanding (Chironico, 1350 m and Nationalpark, 1900 m): they are much smaller than the other estimates. This is not the case under cover. These are high altitude sites, so high altitude seems to be linked to temperature distributions having

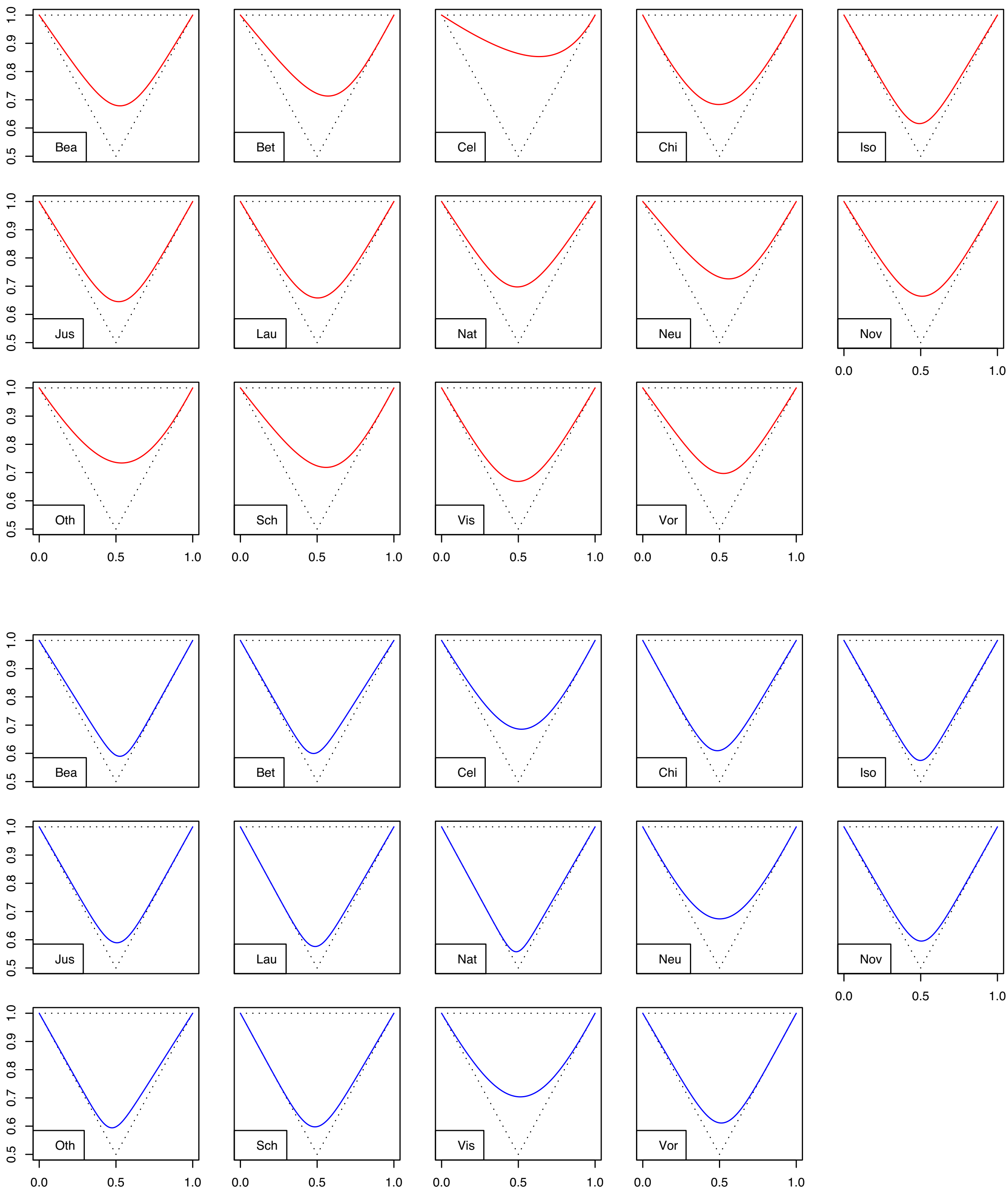

Fig. 4. Fitted Pickands dependence functions for the maximum series (above) and minimum series (below). The dotted lines are the bounds (the upper bound corresponds to independence, the lower to complete dependence).

finite upper end-points. Middle altitudes prevent scale parameters from being lower than −0.25, so the upper end-point will nevertheless be quite far from the bulk of the data. The dependence parameter ρ is also linked to the altitude: whereas below 1200 m a.s.l. eight sites out of nine have a dependence parameter in the interval [0.27, 0.42], three sites out of five above this altitude have ρ outside this interval, showing weaker extremal dependence for the maximum temperatures. Concerning the differences between the asymmetry parameters, considering only those that are clearly non zero, we notice that they increase with the altitude, suggesting that altitude is necessary for the asymmetry due to the effect of the canopy to express itself. Our results show that the impact of the canopy on the highest maximum temperature values increases with altitude.

Extreme slopes (either less than 14% or at least 68%) allow heavy- or light-tailed distributions, whereas middle slopes (between 27% and 58%) favour short-tailed distributions. Indeed, below the canopy, the three shape parameters that can take positive values correspond either to gentle (between 7% and 14%) or to steep slopes (68%), whereas the very negative estimates occur for middle slopes (27%, 34% and 58%). The analysis of dependence parameters shows that a middle slope is necessary for ρ to exceed a value of around 0.4; in other words, a middle slope is required for lower dependence, corresponding to the forest having a significant insulating effect on extreme maximum temperatures. The estimated Pickands functions confirm this: the five highest functions correspond to slopes between 27% and 66%. Moreover, except for three sites, these parameters are all increasing under 34% and decreasing above. The differences between the asymmetry parameters indicate that when the dependence is weaker (middle slopes), an asymmetric model is essential, whereas data from the sites where the dependence is stronger (gentler and steeper slopes) look very close to symmetry.

The orientation essentially impacts the dependence structure: the dependence parameters and the Pickands estimates vary more within northerly oriented sites than for those with a southerly orientation; the dependence structure is more variable in the first case. Indeed, the impact of the forest on extreme maximum temperatures tends to be moderate at southerly oriented sites, whereas, at northerly oriented sites, it can be both weaker and stronger.

Looking at the forest species, sites with conifers have negative shape parameter estimates at both stations, so the canopy maintains the shape of the distribution, whereas sites with beech have negative estimates under canopy, suggesting that beech forests diminish the more intense maxima. The dependence parameter estimates are lower for the oak forests, implying a higher extremal dependence. The beech and conifer forests have estimates that vary more than other forests and so have less impact on the dependence structure. The difference between the asymmetry parameters shows that except at Beatenberg the presence of beech is necessary for the behaviour to be asymmetric: at extremal temperature levels, without beech, the regimes under cover and in the open will be similar. In this case, the forest may have a sheltering effect on average temperatures, but not on the occurrence of high maximum temperatures.

Concerning soils, mull humus seems to be the only soil type that allows the cover to modify the extreme regime, i.e., to prevent the occurrence of extreme maximum temperatures. Indeed, for the majority of the sites, a mull humus implies the fitting of an asymmetric model to the maximum, whereas the other soils should agree with a symmetric model, the exception being Celerina.

The dependence parameter is lower in former coppices than in high forests, indicating a stronger dependence with the open field, or a weaker impact of the forest cover on the extreme maximum temperatures. This is confirmed by the Pickands estimates.

Concerning the relation of minimum temperatures with slope, our results show that the shape parameters under the canopy form two groups: slopes gentler than 34% have estimates that are lower than slopes between 35% and 68%, and at 80% the estimates become lower again. This suggest that the gentler the slope, the shorter the tail and hence the more exceptional are extreme minimum temperatures. At the open-field stations, there seems to be a mix of two behaviours, depending on the slope: if gentle ($\leq$4 %), it has no significant impact; if steep ($\geq$27 %), the estimates increase with the slope, indicating that a steeper slope tends to move the distribution closer to a light tail. The dependence parameter estimates again show two types of behaviour, but not in this case determined by the intensity of the slope. In one case, the asymmetric model does not look necessary, whereas it is for the other case, as also is a dependence parameter that increases with the slope, showing more extremal dependence of the minimum temperatures with gentler slope. Thus when the canopy has an insulating effect on the extreme minimum temperatures, this effect is stronger for steeper slopes.

Orientation plays a major role for the minimum temperatures: the dependence estimates are clearly lower when the sites are southerly oriented, meaning that the dependence between the stations is stronger, i.e. the impact of the forest cover is weaker on extremely low minimum temperatures. The Pickands estimates confirm this: the only three sites that clearly exceed 0.6 are northerly oriented.

The shape parameter estimates show that the sheltering effect of conifers is stronger than that of the other species: in conifer forests, the tail of the extremal distributions is shorter than in the others. Concerning the dependence parameter, several points must be mentioned. First, the value of Neunkirch is outstanding and difficult to interpret. Second, the conifer forests estimates show a great discrepancy whereas the others are very regular, indicating that within conifer forests another feature governs the dependence in the extreme minimum temperatures. Finally, in the deciduous forests, the extremal dependence gets stronger from oak to beech forests with beech and silver fir forests inbetween. The oak forests show a positive difference for the asymmetry parameters, indicating that the density is slightly oriented toward the open field whereas the opposite occurs with beech. The conifer forests once again show very different patterns, suggesting the importance of features such as orientation, slope or soil.

The presence of calcareous soil makes the tail of the minimum densities shorter under cover. A slight trend is present in the differences of the asymmetry parameters: this tends to be positive for the podzolic soils but negative for the mull humus, indicating an opposite asymmetry depending on the type of soil. If podzolic, the probability density function at extremal level is higher in the open field, whereas with a mull humus, it is higher under cover. Thus within forests with podzolic soils, the sheltering effect of the canopy seems efficient for extremely low minimum temperatures, whereas within forests with mull humus, the cover seems to favour the occurrence of such temperatures.

The impact of the management system on minimum temperatures resides in the asymmetry only: within former coppices, a symmetric model would fit the data quite well, whereas within high forests, the difference can be positive or negative, but it is always bigger than within former coppices and so indicates the effect of the forest: if the difference is positive, the cover prevents the occurrence of extremely low minimum temperatures, whereas if it is negative, it will tend to favour them.

5. Conclusions

This analysis of an atypical dataset allowed us to draw several conclusions about the roles played by the different features of the sites in the occurrence of extreme atmospheric temperatures. When interpreting the results we must, however, keep in mind that the site features are correlated.

Altitude plays a role essentially only for the maximum temperatures: if high, the tail is shorter and the extremal dependence weaker. Thus at high altitudes, extremely high maximum temperatures are relatively less likely to occur, and extreme maximum temperatures under cover depend less on those in the open than at lower altitudes, indicating that the forest cover sheltering effect seems to be more efficient at higher altitudes. The slope seems to have a different impact on the maximum and on the minimum. With a middle slope, the maximum tail is shorter and the extreme maxima are less dependent, whereas the minimum tail will be shorter with a gentle slope and the extreme minima will then be more dependent. This means that the insulating effect is efficient for extremely high maximum temperatures in the first case, whereas it is less efficient for extremely low minimum temperatures in the second case. Finally, in both cases, extremely high maximum and low minimum temperatures are less likely to occur. Orientation plays a role essentially only for the minimum temperatures. A southerly orientation increases the extremal dependence, meaning that south-oriented forests have a lower impact on extreme minimum temperature: during the coldest nights, the difference between open field and below canopy is not very high for the south-oriented forests. The impact of the different types of forest is more complex but the conifers isolate more than other types for both extreme maximum and minimum temperatures.

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